Enabling or Accelerating? The Role of Venture Capital in the Innovation Life Cycle.

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This paper investigates how venture capital investors (VCs) affect the generation of intellectual property rights, such as patents, of their portfolio firms. Using a unique European dataset comprising firm-, patent-, and investment-level data on about 9.600 firms between 1995 and 2015, we assess four groups of firms distinguishing VC versus non-VC-backed and previously patenting versus non-patenting firms to establish the actual functioning of VCs. We deploy multiple econometric techniques to differentiate the (i) enabling and (ii) accelerating role of VCs: We find (i) previously non-patenting firms to increase patent quantity, while (ii) previously patenting firms increase patent quality. Our study provides new evidence on the role of VCs for firm-level innovation.

JEL Classification: D23; G24; L26; O32
Keywords: Venture Capital, Intellectual property, Patents, Startup activities

1 Introduction

For stimulating innovation and growth, it is essential to provide an economic setting that encourages investment and engagement in innovative activities (e.g., Schumpeter 1942; King and Levine 1993). A sound financing environment is particularly crucial for young ventures. These firms are particularly dynamic market participants featuring the highest growth rates, disruptive potential, and trigger important knowledge-spillovers (e.g., Schnitzer and Watzinger 2022). Yet, their financing processes are accompanied by severe information asymmetries and uncertainty. Venture capitalists (VCs) are specialized types of investors taking the leading role in financing these young innovation-oriented firms (Amit *et al.* 1998; Berger and Udell 1998; Gompers and Lerner 1999; Hellmann and Puri 2002) and partially overcome agency issues through active involvement in the management (Casamatta 2003; Bertoni *et al.* 2011). To alleviate some information asymmetry, target firms themselves are found to signal their ability to generate future income by initiating pre-investment intellectual property rights, such as patent filings (Häussler *et al.* 2012; Hsu and Ziedonis 2013). Thus, by identifying and fostering the most innovative ventures, VCs should contribute largely to innovative processes.

Surprisingly, the overall contribution of VCs to their targets' innovative activities does not seem to be straightforward. Many studies suggest an enhancing effect of VCs on patenting firms, implying that target firms increase the amount of patents filed after the VC steps in (e.g., Samila and Sorenson 2011, Popov and Roosenboom 2012, Kelly and Kim 2018). Others find that VCs push for rapid commercialization of their targets' innovation output instead of fostering innovative potential in the long-run (e.g., Engel and Keilbach 2007; Caselli *et al.* 2009; Arqué-Castells 2012). One potential explanation for these contradicting findings might be that the fundamental objective of VCs ultimately remains the maximization of returns on their private investments. Further, isolating the actual roles of VCs in the invention processes is non-trivial and requires detailed information on the timing of investments and inventive activities.

As our main contribution, this paper disentangles the most fundamental roles of VC investors on the post-investment innovative performance of their target firms. More specifically, we investigate complementary roles of VC investors related to the post-investment patenting activities of their targets. The roles are: 1) Enabling: A positive effect of VC investments on the long-run patenting output and 2) Accelerating: A positive effect of VC investments on the long-run patenting output of targets that already patented prior to receiving VC. In addition to this, we put a special emphasize on the exact timing of firms patenting activities, as short-term effects of VC investments are unlikely to reflect true enabling or accelerating but rather reflect a change in the commercialization strategy of target firms.[1] To assign these characteristics to the VC activities, this paper provides new evidence on the following questions: Does VC involvement

[1]Furthermore, the absence of a positive effect of previously patenting firms would be in line with a selection effect of VC investors, which has been extensively discussed in prior literature (e.g., Krishnan *et al.* 2011). Our analysis, however, focuses on the post-investment patenting behavior of target firms.

have an effect on the amount of patents filed by target firms and if so, what is the timing of this effect? To answer these questions use several econometric techniques that we deploy on a matched sample of pre-VC patenting firms and non-patenting firms to comparable patenting and non-patenting firms that do not receive VC at any point in time.

Comparing these different roles of VC on their targets' innovative activities is challenging for several reasons. First, unlike most studies we have to follow target firms along the early stages of their lifecycle. A precise evaluation of pre-investment activities is thus equally important as thorough documentation of post-investment outcomes. Furthermore, innovation dimensions need to be comparable across time to evaluate their development after initial investment. We tackle this issue by relying on detailed firm-level patenting data. Previous literature has shown that patenting activities are relevant in the context of young, innovation-oriented VC target firms (Howell *et al.* 2020). Third, there are essential differences among patenting, non-patenting as well as ventures that eventually receive VC and those that do not receive these investments. To obtain more precise estimates on the actual post-investment patenting behavior, we thus follow a multi-stepped matching approach using a large set of firms from multiple European countries. More specifically, we generate four groups of firms. We first distinguish targets regarding their pre-VC patenting activities. Subsequently, we assign each of these firms a counterparty with comparable observable characteristics, such as their patenting behavior, country of origin, industry, age, size, and growth dynamics before receiving initial VC investment. Controlling for these covariates mitigates concerns regarding the obvious endogenous decision of VCs whether to invest into a firm or not. Still, VC targets and their counterparts are likely to differ along other unobservable characteristics. Although this selection issue can never be fully resolved, we make use of a switching regression with endogenous switching (e.g., Chemmanur *et al.* 2011), in which the calculation and integration of the inverse mills ratio addresses this concern.

Our final dataset combines firm-level balance sheet data (ORBIS) with information on individual rounds of VC investment (Refinitiv Eikon) and European patent data (PATSTAT). It comprises more than 9.500 firms from the EU15 countries in all relevant industries for a time-span of more than 20 years, starting in 1995.

We find that it is indeed crucial to distinguish between VC funded firms that have been involved in patenting activities prior funding and firms that have never filed for a patent before, for VCs take on different roles in these scenarios. A semi-parametric survival analysis shows that VCs enhance the patenting activity of the target firms that have not filed for patents prior funding significantly when compared to their non-funded counterparts. This result holds for the extensive as well as for the intensive margin. We find that the instantaneous probability to file for a patent is 3.3 times higher for a VC funded firm compared to a firm without funding in the control group. We do not find similar effects for the subset of firms that have been patenters before they received their first round of funding. When compared to their non-funded counterparts we do not find that those firms file for significantly more patents, neither in the short- nor in the long-run. This indicates that VCs do not play an accelerating role for those firms. Taking a closer look at the distinct timing of the patent applications in the non-patenting group allows us two pin down two major conclusions: VCs use their already existing innovative potential in the short-term, more precisely extract patents shortly after the initial round of funding, but they also reinforce those firms to be innovative in the long-term, thus playing the role of enablers. Examining distinct timing does not change the effect for patenting firms. When compared to their counterparts at any point in time after the initial round of funding we do not find significant differences in the amount of patents filed. Nevertheless, those results contradict the conclusion that VCs push their targets towards a rapid commercialization thereby inhibiting innovative progress in the long-run.

The remainder of the paper is structured as follows. Chapter 2 provides a brief overview on the contradicting findings of previous literature and presents our conceptual framework. Chapter 3 introduces the data and the research design. Chapter 4 provides the empirical results and Chapter 5 concludes.

2 Literature and methodological approach

2.1 Related literature

Our analysis contributes to the rich literature on VC financing by taking an encompassing view which investigates the involvement and influence of venture capitalists on their targets. In this context, we extend the literature on the effects of VC financing on firm dynamics and growth. A broad range of analyses provides evidence for an enhancing effect of VC involvement on a variety of productivity-related firm performance indicators (Jain and Kini 1995; Manigart and Van Hyfte 1999; Burgel *et al.* 2000; Bottazzi and Da Rin 2002). Moreover, VC financing plays a central role for innovative output, since it acts as a close substitute for firm-level R&D investments (e.g., Kortum and Lerner 2001, Hirukawa and Ueda 2011). Our analysis focuses on innovative performance as a specific driver of economic growth and uses patented inventions as one distinct dimension of it. When considering patenting as an outcome variable, most studies compare patent activities among firms depending on whether they have received VC financing or not. In contrast to the overall and dominant enhancing effect that is found for VC on firm performance indicators there is no general notion in the literature concerning effects of VC funding on firm-level innovative activities. Some studies suggest an enhancing effect of VC on patent filings (e.g., Samila and Sorenson 2011, Popov and Roosenboom 2012, Kelly and Kim 2018). Yet, others find VCs to shift their focus to sales as soon as the inventive process is completed, leading to a decline in patented inventions after the initial VC investment (Engel and Keilbach 2007, Caselli *et al.* 2009, Arqué-Castells 2012).

Our analysis provides new evidence on the effect of VC investment on patent-based innovation measures by taking a specifically granular view on the close and dynamic relationship of VCs and their targets. A major contribution of our analysis is thereby to disentangle the mechanisms behind the average effects of VC on patenting activities. Specifically, we analyze whether different patterns can be attributed to firms with patenting activities prior to the initial investment and to firms that do not patent before, i.e., whether the average outcomes are driven by VCs selecting firms that already patent prior to initial investment or whether the VC enables firms to engage in patenting. Given the mixed evidence concerning the role of VC on patenting outcomes, distinguishing among these lines is important for providing a better understanding on the actual implications of VC engagement for their targets' innovative performance.

Our paper contributes to an emerging strand of literature that combines observations from before and after the initial VC investment its involvement in the target firm. For example, Baum and Silverman (2004) analyze whether VCs select innovative firms or whether they foster initial engagement in innovative activities. The authors conclude that the role of VCs is a combination of scouting strong technology and coaching via management skills. Similarly, Häussler *et al.* (2012) construct a matched sample of German firms which differ only with respect to whether they eventually receive VC or not. They show that target firms are only different prior to VC investment when it comes to their patenting activities, whereas this difference vanishes once the VC steps in. Our approach deviates from these previous analyses in fundamental aspects. We compute a matched sample that distinguishes patenting and non-patenting firms for both VC-backed and non-VC-backed firms from a wide range of countries. We match respective firms on time-varying and time-invariant firm characteristics from the years prior to the initial investment. The resulting four different types of firms allow us to obtain detailed insights on the mechanisms which constitute the average differences in post-VC patenting activities. This way, we are able to gain new insights on the VCs' role on firm-level innovative output by testing whether VCs rather serve as short-term extractors or furthermore play the role of long-term accelerators or enablers of inventive activities. Moreover, by utilizing granular quantitative and qualitative information on firms' patented inventions, we are able to provide a more nuanced view on the post-VC patenting activities, which allows us to elicit VCs' preferences in greater detail.

2.2 Conceptual framework

Enabling versus accelerating: The following subsection describes the conceptual idea behind our analysis. It provides the basis for outlining our empirical strategy. Our main proposition is that the average effect of VC investments on patenting activities, Δ_{avg}, can be decomposed into two separate components. We first consider the patenting activity of VC-backed firms, V, by comparing patenting activities before (V_{pre}) and after (V_{post}) initial VC financing, i.e., $\delta_V = V_{post} - V_{pre}$. Analogously, we consider the patenting activities of firms without VC-backing, N, following the same intuition, i.e., $\delta_N = N_{post} - N_{pre}$. By definition, these firms do not receive

VC at any point in time. Conceptually, the differentiation between pre and post VC thus reflects a hypothetical investment: Comparing pre- and post VC financing levels for a firm j that does not receive VC financing (N) refers to the situation in which an identical firm, i, actually receives VC financing. In both cases, patenting outcomes are also affected by firm-, industry-, country-, and time-specific effects (X'). In our estimations, we control for these factors such that they are arguably the same for VC-backed and non-VC-backed firms. For simplicity, we therefore assume in the following that $X' = X'_V = X'_N$, such that these factors cancel out. Hence, Δ_{avg} is the average effect of VC investment on the patenting activity of VC-backed firms relative to firms without VC financing:

$$\Delta_{avg} = \delta_V - \delta_N = (V_{post} - V_{pre} + X'_V) - (N_{post} - N_{pre} + X'_N) \quad . \tag{1}$$

A priori, the properties of the average effects for firms with or without patenting activities prior to the initial VC investment are not clear. Intuitively, for firms without any patenting activities, this effect cannot be negative. We define the *enabling* effect as the situation in which VC financing ignites patenting activities for firms without patenting activities prior to VC financing. In contrast, for ex ante patenting firms, the effect of VC investments on patenting outcomes can be positive, negative, or zero. For simplicity, we collectively refer to this as the *accelerating* effect.[2] This way, we follow the general consent in the literature ascertaining an enhancing effect of VC financing on firm-level productivity outcomes.

To investigate the presence of an *enabling* and/or *accelerating* effect of VC financing on patenting outcomes, it is necessary to separate firms regarding their patenting activities prior to initial investment. The overall effect, as defined in Equation (1), can be re-written as:

$$\Delta_{avg} = \delta_V - \delta_N = \left[(V^0_{post} - V^0_{pre}) + (V^1_{post} - V^1_{pre})\right] - \left[(N^0_{post} - N^0_{pre}) + (N^1_{post} - N^1_{pre})\right], \tag{2}$$

which takes into account whether firms engage in patenting activities before initially receiving VC financing (1) or not (0). The average effect of receiving VC financing on firms' patent activities δ_V equals the unweighted average effect of firms without (V^0) and with (V^1) patenting activities prior to the initial financing round. Rearranging Equation (2) allows to test the effects of VC financing on patent outcomes, conditional on pre-VC patenting activities. Firms that do not receive VC (N) serve as a reference group, which is similarly affected by market developments. As illustrated in Panel A of Figure 1, firms thus can be categorized into the four groups: V^0, V^1, N^0, and N^1.

- Insert Figure 1 here -

For the enabling effect, the components V^0_{pre} and N^0_{pre} cancel out, since these two firm types

[2]Note that a negative accelerating effect could be interpreted such that the patenting activities of firms prior to VC investment were conducted as a signaling device.

do not patent prior to VC financing, i.e., $V^0_{pre} = N^0_{pre} = 0$. Panel B of Figure 1 illustrates the conceptual idea of the two main effects graphically. Following this, the *enabling* (Δ_{ena}) and *accelerating* (Δ_{acc}) effects are:

$$\Delta_{ena} = (V^0_{post} - N^0_{post}) - (V^0_{pre} - N^0_{pre}) = (V^0_{post} - N^0_{post}) \qquad \text{and} \tag{3}$$

$$\Delta_{acc} = (V^1_{post} - N^1_{post}) - (V^1_{pre} - N^1_{pre}) \qquad . \tag{4}$$

Timing of the effects: The actual timing of patenting activities is central for gaining a deeper insight on the actual role of VCs in the innovation life cycle of their targets. The enabling and accelerating effects distinguish two complementary and mutually exclusive approaches to evaluate the effect of VC engagements on patenting activities. Yet, they are silent about one important but conflicting aspect: patenting is a firm-level outcome that is the product of medium-termed inventive activities. In other words, patent applications are the results from research and development in the past and only realize over time: There should be a substantial time gap between the initial idea creation and the development of a patentable invention. Plausibly, it follows that a patent application within the first year after the initial VC investment is unlikely to refer to a technological invention that originated within this very first year. Instead, it is fairly likely that the development of this invention was already initiated prior to the VC investment.

The time gap between idea creation and patent application has important implications for our conceptual design. Consistent with the fact that average cycle times of new product lines take about 36 months (Griffin 1997; Cankurtaran *et al.* 2013), we assume that the development of an entirely new technology, which is eventually patented, takes on average at least two to three years. Consistent with this, we expect that the initial idea and research about a new technology of the average patent that was filed within the first years after initial VC investment already existed prior to the investment. Conversely, patents filed three or more years after the investment are likely to be based on ideas generated after the initial VC investment.

From a conceptual perspective, patenting activities therefore have to be interpreted differently depending on the actual timing of the patent filing relative to the investment date. Any change in patenting activities as defined in Equations (3) and (4) within the first years after VC investment is likely to reflect - at least in part - the commercialization effect described in the literature (e.g., Caselli *et al.* 2009, Lerner and Nanda 2020). This holds in particular for the first two years after VC investment. In this period, it is unlikely that any change in patenting activities would reflect that the VCs actually influence the idea creation of the target firm. The VC rather induces the patenting strategy, i.e., the fact that already existing inventions are pursued to be legally protected by a property right. In contrast, one could associate changes in patenting with the enabling or accelerating roles of VC more directly, once these changes occur after a minimum time lag of two to three years. For these reasons, we put a special emphasize on the actual timing of the patenting filings in our empirical analyses.

3 Data and empirical strategy

3.1 Dataset construction

Our sample contains data from mainly three sources. The basic firm-level financial and bibliographic data is obtained from Bureau van Dijk's ORBIS database, which covers the universe of firms from the majority of European countries. Because the coverage of distinct countries varies across time and in order to avoid selection biases, we collect data for the EU15 countries beginning with the year 1995.[3] We augment this information with detailed data on patenting and VC. Patent data is obtained from PATSTAT, which contains in-depth legal and other related properties covering the universe of patents filed in Europe. We extract VC data from the Refinitiv Eikon database, which provides detailed information on individual funding rounds per firm. We utilize these three sources to obtain four different groups of firms, which correspond to the groups V^0, V^1, N^0, and N^1 in Figure 1.

Matching approach: Our empirical analysis compares post-VC patenting (and other real economic activities) across these four groups. However, whether or not a target firm receives VC investments is an endogenous decision by respective investors, i.e. it is plausible to assume that observable firm characteristics differ between VC targets and other firms. To mitigate concerns regarding these differences, we deploy a matching approach that links VC targets to firms with similar observable pre-investment characteristics.

Determining the pre-investment time window for firms that actually do not receive VC investments is non-trivial. In fact, the majority of firms does not receive VC at any point in time. To solve this, we first select those firm-year observations from non-VC-backed firms that can potentially be paired to VC recipients as they are equivalent with respect to the country of residence, industry affiliation (i.e., NACE main category), and founding year. On top of this, we impose that firms can only be paired depending on whether they have previously filed any patent application for any given calender year. This gives us a set of VC-backed and non-VC-backed, patenting and non-patenting firms that can potentially be paired. We thus match these firms, namely VC-backed and non-VC-backed firms, using Coarsened Exact Matching (CEM) according to pre-defined matching characteristics. We match based on firm size (log assets), asset growth, a more granular industry level (4-digit NACE), and the number of patents filed. For VC-backed patenting firms, these variables are computed for the average of the three years prior to initial VC investment. In contrast, for non-VC-backed firms, we compute these variables on the basis of three-year rolling windows. The matching procedure groups firms into stratas that

[3] The EU15 countries are the members of the European Union at the first sampling year: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden. We exclude Luxembourg because its economy primarily comprises financial firms.

may contain any number of VC-backed, non-VC-backed, patenting, or non-patenting firms. We only keep those stratas that comprise at least one VC-backed firm. To avoid heavily unbalanced group sizes, we select the closest non-VC-backed neighbor of any VC-backed firm within the respective stratas.

Following this procedure provides us with symmetrically-sized groups of patenting and non-patenting firms as defined in Equations (3) and (4), i.e. $(V^0,\ N^0)$ and $(V^1,\ N^1)$. Each firm has a matching partner that is comparable with respect to the location, industry, age, size, asset growth and pre-VC investment patenting activities. For non-VC-backed firms, the pre-VC investment period refers to the years before their matched VC-backed pair-firm receives financing for the first time. Table 1 provides summary statistics on the matched sample. In line with our matching approach, there are no statistically significant differences among these groups along key observable characteristics before the initial VC round.

- Insert Table 1 here -

3.2 Descriptives

The final data set contains 84,689 firm-year observations, comprising 9,614 individual firms. By construction, half of the sample receives VC funding at some point in time. Around 10% of those firms filed for at least one patent before the matching period t=0. Our sample covers a representative time span of 20 years (1995-2015) that includes informative events such as the bursting of the Dotcom Bubble in 2001, the Global Financial Crisis in 2008/2009, and the European Sovereign Debt Crisis in 2012. The inclusion of such events enables us to point out the role of VCs in the innovative progress of their portfolio firms during distinct macroeconomic events while the time span covered allows us to explicitly investigate the involvement of the VC industry as a whole in Europe. VC activity is concentrated on the largest economies in our sample, e.g., around 60% of the firm pairs are located in Germany, France, and the United Kingdom.

- Insert Table 2 here -

Regarding the sectoral distribution, our data set comprises firms from almost all industries. However, most observations are clustered in industries known for a high propensity to patent or to attract VC financing, such as information and communication (26%), manufacturing (21%), and professional, scientific and technical activities (20%). By construction VC funded and non-VC funded firms are equally distributed across industries. The distribution changes when only patenting firms are considered. Those firms are concentrated in manufacturing (46%) and professional, scientific and technical activities (32%).

- Insert Table 2 here -

50% of the firms in our sample have been founded until 2002, while the rest was founded in the remaining 12 years. Our sampled target firms are on average fairly young, with pre-VC patenting firms being slightly older (8.1 years) as compared to pre-VC non-patenting targets (7.2 years). This is well in line with the main idea of VC involvement in young, innovative and external finance dependent ventures, whereas it reflects that patenting may require time and involvement. Show some sector distribution – could be that non-patenters are from different industries. Further, VC targets with pre-investment patenting activities obtain more investment deals (1.8) compared to non-patenting counterparts (1.5). This difference is statistically significant but in economic terms rather small. Moreover, the difference in investment amounts collected during the initial VC round and overall are insignificant. This suggests that the firms in our sample are relatively similar, conditional on obtaining VC investment. These observations are consistent with the fact that VC select potential targets and focus on observable (i.e., patenting activities) as well as unobservable factors.

- Insert Table 3 here -

With regard to the main question, whether VCs serve as extractors and enablers or accelerators in the innovative progress of their target firms, simple t-tests provide first insights. In this context we consider the intensive as well as the extensive margin. Are VC funded firms more engaged in overall patenting activity and do they file for more patents post funding than their non-backed counterparts? In the first case concerning previously non-patenting firms (V^0 and N^0) Panel A of Figure 2 shows that VC backed firms are significantly more engaged in overall patenting. Each year 1% of non-funded firms patent, while between 5% and 6% of the funded firms file for at least one patent up until eight years post funding. Panel B of Figure 2 displays, that this finding cannot be replicated for the sample of previously patenting firms. There is no significant difference between the firms that received VC funding and their non-backed counterparts in the eight years following the initial VC investment.

- Insert Figure 2 here -

T-tests concerning the intensive margin show the same pattern, thus hinting towards an enabling effect for VC target firms that have not been patenters prior funding. Panel A of Figure 3 shows that they file significantly more patents than their non-backed counterparts throughout the whole time-span observed. Panel B of Figure 3 underlines the findings of Figure 2 for the two groups of previously patenting firms (V^1 and N^1). The funded firms do not file for signifcantly more patents when compared to the control group. Thus, we do not find first evidence pointing towards an accelerating effect of VCs for previously patenting firms.

- Insert Figure 3 here -

3.3 Estimation Approach

Enabling Effect: The conceptual framework suggests that the enabling and accelerating effects are mutually exclusive concepts, implying that one single firm may not be subject to both effects. In addition, the specific differences in pre-VC patenting activities ask for two separate analyses, applying two different estimation approaches. Panel B of Figure 1 illustrates the enabling effect graphically and shows that we compare the post-VC patenting behavior of two groups, which have not filed for patents prior to the initial VC investment (i.e., $t = 0$), that is V^0 and N^0. Since this implies that there is by definition no variation in pre-VC patenting activity, we have to select an estimation technique that exclusively relies on differences in post-VC patenting activities.

We chose a survival analysis for estimating the effect of VC on the patenting activity for V^0 and N^0. In comparison to using OLS estimates, this approach has two main advantages. The first one addresses a drawback of the Bureau van Dijk's ORBIS database, namely that we are not able to see whether firms drop out of the dataset due to exiting the market or simply because they are not observed anymore. Moreover, we only observe firms until the end of 2015, without any knowledge concerning their behavior in following periods. This indicates a right-censoring problem which we are able to address using survival estimates. A second advantage concerns assumptions of the distribution of time. Linear regressions work with the underlying assumption, that residuals are distributed normally and thus the timing of patent applications conditional on x_j is assumed to follow a normal distribution. This assumption is strong and not likely in our context. Thus, a Cox proportional hazard model (Cox (1972)) with the following regression equation is a fitting approach to examine the enabling effect:

$$h(t|x_j) = h_0(t)exp(\beta_1 x_1 + \beta_k X' + \alpha_c + \alpha_j + \alpha_{ct}) \ . \tag{5}$$

h_0 is the baseline hazard which does not need to be estimated in the Cox proportional hazard model and consequently can take any form in order to avoid misspecification. The hazard rate $h(t|x_j)$ represents the instantaneous probability of a patent application for each firm and is determined by a set of covariates. Specifically, this includes a dummy variable VC_i which is equal to one for VC funded firms and zero for their non-backed counterparty. X' is a vector of control variables that includes observable, time-varying firm characteristics, i.e., firm size age, and profitability. The coefficient of interest is β_1, which reflects the differential probability of a patent application of a VC-backed firm relative to its matched non-VC-backed counterparty. α_c, α_j, and α_{ct} are country, industry and country-year fixed effects. In a first step we need to set up the dataset such that firms drop out of the analysis after their first patent application post funding for the purpose of examining the enabling effect.

Accelerating Effect: Panel C of Figure 1 illustrates the accelerating effect of VC. The key difference as compared to the analysis of the enabling effect is that treated and non-treaded firms (i.e., VC-backed and non-VC-backed firms) file at least one patent during the years prior to the initial VC investment, i.e., V^1 and N^1. Our empirical approach has to take these activities into account in order to estimate the average accelerating effect of VC on the patenting activities of firms that already patented prior to the initial VC round. Since the data is structured similar to an event study analysis, including a differentiation among treated and non-treated as well as pre- and post-event time periods, we are able to apply a difference-in-differences approach. Here, the first round of VC investment marks the treatment variable, whereas treated and non-treated firms refers to the fact whether a firms eventually receives VC or whether it is a matched sample firm without VC financing. Our methodology follows previous work (e.g., Petersen 2009) by including a whole set of fixed-effects and adjusting the standard errors for correlations within clusters. In all estimations, we report standard errors clustered at the firm level. We estimate the following set of fixed effects regressions for the matched sample of pre-VC patenting firms:

$$y_{it} = \alpha_c + \alpha_j + \alpha_{ct} + \beta\, VC\text{-}funding_{it} + \gamma' X_{it} + \varepsilon_{it}\ , \tag{6}$$

where i indexes firms, j indexes industries, c indexes countries and t indexes years.y_{it} represents our dependent variable, which is the logarithm of the number of patent applications filed; α_c, α_j, and α_{ct} are country, industry and country-year fixed effects, X is a vector of control variables, identical to the control variables used in the survival analysis, and ε represents the error term. Our main coefficient of interest is represented by β. The dummy variable VC-funding is equal to 1 if a firm receives VC funding for the first time in the observation period t and all subsequent periods and zero otherwise. Essentially, this dummy variable can be rewritten as $VC\text{-}funding_{it} = VC_i \times post_{it}$, with VC_i being a dummy variable that is equal to one for any firm i that eventually receives VC financing and $post_{it}$ being a firm-specific dummy variable that equals one for all years after initial VC investment is received by firm i. Hence, β captures the average additional effect of receiving VC on firms' patenting activities. If an accelerating effect through VC involvement exists, this coefficient will be positive and significant. For robustness, we will augment this specification in two alternative ways. These estimations serve mainly two purposes: i) by decomposing the treatment effect (i.e., β_1 from Equation 7) we gain a better understand on the timing of the effects and ii) the estimates on the pre-treatment period serve as a robustness test on parallel trends in the patenting behavior between VC-backed and non-VC-backed firms from the comparison group. Specifically, we estimate the following two specifications:

$$Y_{it} = \alpha'_t + \alpha'_i + \beta_1(VC_i \times Pre_{it}^{\text{-2,-1}}) + \beta_2(VC_i \times Post_{it}^{0,1}) + \beta_3(VC_i \times Post_{it}^{\geq 2}) + \gamma' X_{it} + \varepsilon'_{it} \tag{7}$$

, and

$$Y_{it} = \alpha''_t + \alpha''_i + \sum_{S=-2}^{-6} \beta_1^S(VC_i \times Pre_{it}^S) + \sum_{S=0}^{6} \beta_2^S(VC_i \times Post_{it}^S) + \gamma'' X_{it} + \varepsilon''_{it}\ . \tag{8}$$

where y_{it}, X_{it}, VC_i, $Post_{it}$ are specified equivalent to Equation (7); α_t and α_i denote time and firm fixed effects; Importantly, we estimate these equations on a sample with a symmetric time window +/- six years around the initial VC investment year. Moreover, in Equation (8) we add $Pre_{it}^{-2,-1}$ which is a dummy equal to one for any observations within the two years prior to the initial VC investment. Further, we decompose the treatment indicator, $Post_{it}$, into i) the initial effect of a VC funding for the first two years after initial investment, i.e., the years $t = 0$ and $t = 1$, and ii) the medium- to long-termed effect for the five subsequent years, i.e., the years $t = [2, 6]$. Thus β_1, β_2, and β_3 in Equation (8) capture the average difference in debt ratios between IP pledging firms and their matched partners, *relative* to the years $t = [-6, -3]$. Equation (9) decomposes the effect on a year-by-year basis: $Post_{it}^S$ and Pre_t^S are equal to one (and zero otherwise) for all observations in S years after or prior to initial VC investment, where $S = [0, 6]$ or $S = [-6, -2]$, respectively. In this specification, the last year prior to the VC investment is the reference time period.

The extracting effect and distinct timing: While the enabling and the accelerating effect are mutually exclusive concepts, the extracting effect can occur for firms that have been patenters prior funding as well as for firms that have not filed for patents before. Given that a company needs a distinct amount of time τ to file for a patent, we assume, that a VC has not contributed to the innovative process, if a patent is filed up until three years (τ=3) post the initial round of funding. If we observe that funded companies only file for patents in this distinct time span and not afterwards, we would interpret this finding such that VCs push for the strategic decision of patenting already existing inventions but not innovative progress itself. If we observe patent applications in the three initial years after VC funding as well as in subsequent years, we argue that VCs are likely to push for rapid patenting on the short-term but also reinforce innovative activities in their target firms in the long-term. In this case, VCs fulfill the roles of extractors and enablers/accelerators.

We employ two different empirical strategies to approach this matter of distinct timing. The first one is to allow for multiple failures in the context of the Cox proportional hazard model used to pin down the enabling effect. We follow Wei *et al.* (1989), thus treating repetitious patent filings within a firm as unordered events, given that one patent application does not necessarily rely on any application that has been filed before. Using this approach enables us to see the distribution of patent filings over time and to compare the results to the survival estimates.

A second solution to identify the distinct timing of patent applications is the switching regression inspired by Chemmanur *et al.* (2011).[4] With this method we ask two hypothetical questions for each point in time prior funding: What would the patenting behavior of VC targets be, had they not received financing and, vice versa, what would the patenting behavior of non-

[4] Chemmanur *et al.* (2011) refer to Fang (2005), Dunbar (1995) and Lee (1978)

funded firms be had they received financing by a VC? The switching regression with endogenous switching mainly comprises two stages. The first stage is a two-step Heckman-type approach. We start by conducting a simple probit estimation, predicting the probability to receive VC funding. We run the regression separately for previously non-patenting firms (V^0 and N^0) and previously patenting firms (V^1 and N^1). The resulting inverse Mills ratio is used as a control for unobservables in the second step, in which the effect of VC funding on the number of patent applications is estimated with a fixed effects regression. The second stage of the switching regression aims to answer the previously asked questions. To do so we compare the actual number of filings with the predicted number of filings for several time spans after funding.[5] Thus, we are able to identify explicit firm patenting behavior separately for each year and can alleviate concerns regarding possible critique towards our matching approach. One might argue that unobservable firm characteristics might influence the decision of the VC to invest into their target firms. Using a two-step Heckman-type approach and the consequential inverse Mills ratio allows us to mitigate concerns that those unobservable characteristics influence the selection of VC targets in the first place.

4 Results

4.1 Baseline Results: The Enabling Effect

We start out by estimating the enabling effect using the Cox proportional hazard model as defined in Equation (6). To do so, we restructure our main sample of pre-VC non patenting firms to a firm-year panel that starts with the first firm-pair year in which the VC target receives initial funding (t=0) and ends with the year in which the firm files a patent application for the first time. We observe 1,062 firms that file for at least one patent, out of which 86% are attributed to VC-backed firms. Table 5 displays the results of the Cox regressions, which test this association in a multivariate setting.

- Insert Table 4 here -

In all columns, regressions estimate the Cox model introduced in Section 3.3 but use different combinations of fixed effects, as indicated in the bottom of the table. Column 4 estimates our baseline specification as specified by Equation (5), including country-, industry-, and country-year fixed effects. Across all specifications, we obtain a large and positive coefficient for our variable of interest, VC. The coefficient is statistically significant at the one percent level and robust to the application of the different fixed effects. It indicates that the instantaneous probability to file for a patent is 3.3 times higher for a VC funded firm compared to a firm without funding in the control group.

[5] We predict the number of filings for VC-funded firms using the resulting values of the second stage for non-funded firms and vice versa.

Estimates on the Cox model show that VC are associated with a much larger average probability of patent filings for VC backed firms after the VC investment. To obtain a first understanding on the timing of patent filings, Figure 4 displays the Nelson-Aalen cumulative hazard estimates on the probability of patent filings for the eight subsequent years after initial VC investment for previously non-patenting firms. The plot confirms that VC-backed firms are generally significantly more likely to file patents compared to their non-VC-backed counterparts.The difference between the two groups of firms is evident throughout the observed time span and widens over time. After eight years around 16% of the VC funded firms have filed for a patent at least once while only around 3% of the matched firms have become patenters.[6]

- Insert Figure 4 here -

4.2 Baseline Results: The Accelerating Effect

To test whether we can attribute VCs with an accelerating effect, we analyze the sample of pre-VC patenting firms. We observe 74% of VC-funded firms to remain patenters after receiving the initial VC round in any subsequent period that we observe. Compared to this, the share of non-VC-backed counterparts that continue patenting is much lower (64%). This difference is statistically significant and robust to using different post-VC time windows.

Table 5 shows regressions estimating the effect of VC investments on their targets' patenting filings (measured in logs) relative to the matched comparison group that did not receive VC. Column 1 displays results on the main specification as defined in Equation (7). The coefficient of the interaction term $VC \times Post$ is positive but statistically insignificant, suggesting that there is no differential patent filing activities after the VC investment between VC-backed and non-VC-backed firms. The insignificant coefficient on the VC variable shows that on average there is also no different prior to the first VC round, which confirms our matching approach. This finding suggests that VCs on average do not trigger an accelerating effect on the patenting activities of their targets.

- Insert Table 5 here -

For robustness, we test this relationship in several ways. First, consistent with the analysis on the enabling effect, Columns II and III distinguish between the manufacturing and non-manufacturing firms. The results are the same as in the baseline estimation which shows that there are no differential effects that are linked to differences in sector-specific patenting-intensities. Further, Column 4 repeats Column 1 but excludes the crisis years 2001, 2008, and

[6] Figures IA1 and IA2 in the Appendix show, that this pattern is stable when only looking at firms with patents that have received at least one citation and at firms with patents that have received more than medium citations. This underlines that the enabling effect is not only driven by firms with marginal innovations

2009. Results are similar to the previous ones and mitigate concerns that recession-specific investment activities account for our baseline finding. Next, to analyze whether the documented effects are not only caused by averaging the VC effects across the entire post-investment period, we estimate Equation (8) in Column 5. We control for firm-specific time-invariant effects by including firm-fixed effects.[7] We find positive but insignificant effects on both post-VC interaction terms, which confirms that there are no differential effects between VC-backed firms and the comparison group both on the short- and the long-term. Further, the insignificant coefficient on the $Pre^{-2,-1}$-dummy serves as first evidence that the two groups move along parallel trends during the pre-treatment period. Finally, we examine the time-structure of the baseline results on the accelerating effect estimating Equation (9). Panel B of Table 5 displays the β-coefficients that track the differences between VC-backed and non-VC backed patenting firms across the symmetrical time window of six years before and after the initial VC investment. None of the coefficients is statistically different from zero, which underlines the previous findings. The two groups of firms seem to move in parallel trends before and after the initial VC-investment. This implies that there is no enhancing effect of VC investment on the patenting activities of pre-VC patenting firms: Our results do not support the accelerator hypothesis of VC investments. In Figure **??** (Appendix B), we confirm that these results are robust to using quality-adjusted patent filings (i.e., by patent citations and the originality index scores). Against this background, it is important to remark that we find no evidence for the idea that VC investors push target firms towards rapid commercialization of patents, which would have a negative effect on the amount of patent applications in the long-term (as suggested in some previous studies, such as Engel and Keilbach 2007).

4.3 Baseline Results: Timing

The switching regression with endogenous switching allows us to answer two "What-if" questions on a yearly basis. What would the patenting behavior of a VC funded firm have looked like, had it not received financing and what would it have been for an unfunded firm, had it received financing. We firstly answer these questions for quantitative features of patenting, namely the amount of patent applications each year. Table 6 shows the results.[8] Panel A displays the logarithm of the actual number of patent applications each year after the initial round of funding for firms without pre-VC patent filings, and compares it to the predicted value, had they not received VC funding. It shows that the actual amount is always higher than the predicted one. For example we see that these firms file on average for more than three times as many patents as they would have without funding in the first year after the initial funding. The difference is statistically significant at the one percent level and robust for all subsequent years. Panel B shows that the opposite is true for the non-backed counterparts. In the first year after a

[7]Including matched-group-fixed effects does not change the results (undisplayed).

[8]Panel A and B of Table 6 and 7 show evidence for firms that have not filed for any patents prior funding, Panel C and D map the results for Patenters.

hypothetical funding, they could have filed for five times as much patents as they did without VC support. This difference is stable and significant on a one percent level for six subsequent years following a potential funding. Those results back up the evidence from the Cox regressions.

- Insert Table 6 here -

The Difference-in-Difference approach in the previous section has not provided evidence that VCs play the role of accelerators in portfolio firms that have been actively patenting prior an initial investment. Panel C in Table 6 validates this finding. It displays the logarithm of the actual number of patent applications each year after the initial round of funding for this subset of patenters and compares it to the predicted value, had they not received VC funding. We do not find a significant difference for those values. Nevertheless, their non funded-counterparts would have profited from VC funding, at least in the six years following the initial investment round. Panel D compares the actual values with the predicted ones and shows that those firms could have filed for 1.35 times as many patents, had they received funding one year before. This difference is significant on a one percent level for the first six years after a hypothetical funding event.

We can also answer the two "What-if" questions for qualitative features of patenting. To find out whether the patents filed are comparably relevant we conduct the switching regression with the sum and the average amount of forward citations received per patent in a time span of five years. Table 7 displays the results for the logarithm of the sum of citations received per patent. Panel A shows that the patents filed for in the first year after the initial investment round receive five times as many citations as they would have, had the firm not received VC support. This difference is statistically significant on a one percent level for all observed years and widens until the seventh year post funding. Panel B shows that the opposite is true and even more pronounced for the non-backed counterparts.

- Insert Table 7 here -

While quantitatively VC funding does not have an impact on the patenting behavior of their previously patenting portfolio firms, the patents filed seem to be more relevant. Panel C of Table 7 shows that funded firms receive significantly more forward citations than they would have received without financing. For example we see that the patents filed for six years after funding receive 1.9 times as many citations as they would have without funding. This finding is consistent over time, statistically significant on a 5 percent level at least and economically relevant when comparing actual and predicted citations. Comparing this result with the findings of Panel C of Table IA1 in the Appendix indicates that the qualitative differences emerge from individual patents and not the whole patent portfolio of VC funded firms. The difference between the actual and the predicted amount of average citations is not significant at any point in time following the initial round of funding, even though it still points in the right direction.

Overall the switching regression with endogenous switching is a helpful tool to validate previous findings and to add more insight on the distinct timing of patenting behavior. While the results support the hypothesis, that VCs act as enablers for firms that have not filed for patents prior funding we find no evidence for an accelerating role of VC, even though the quality of individual patents is significantly higher due to VC support.

5 Conclusion

Previous literature has provided mixed evidence when it comes to the question whether VC financing has an effect on the patent behavior of portfolio firms. While some claim a positive effect on the amount of patent applications (Mann and Sager (2007), Cockburn and MacGarvie (2009), Häussler *et al.* (2012)), others find that VC involvement pushes firms toward a quick commercialization while decreasing innovative output in the long run (Engel and Keilbach (2007); Caselli *et al.* (2009)). We are the first to disentangle the effects of VC on patenting by looking at firms that have filed for patents prior funding and firms that haven't in different ways, thus distinguishing between a possible enabling and a possible accelerating role of VCs. Furthermore we employ techniques that allow us to pin down the timing of the patent applications and to observe qualitative aspects of patenting as well. We provide evidence that VCs act as enablers for firms, that have never been active patenters before they received funding. These portfolio firms file for significantly more patents than their non-funded counterparts and file fore patents that are significantly more relevant. For firms that have been patenters prior funding we find an accelerating effect of the VCs involved in terms of quality, but not in terms of quantity for the patents filed. Nevertheless, we cannot confirm results pointing towards quick commercialization and a long-term decreasing patenting behavior.

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Tables from the main part

Table 1: Comparing matched sample groups during pre-VC phase

Panel A: Firms *without* pre-VC patent filings

	VC-backed (V/N)		**Differences in means**
	V^0	N^0	
Firm size (log. assets)	13.689	13.657	0.032
Age (in years)	7.689	7.673	0.016
Asset growth	1.110	1.107	0.003
Dep. on ext. finance	-0.935	-0.750	-0.185
Current-ratio	1.728	1.775	-0.047
Investments (log. capital exp.)	4.559	4.537	0.022
Patent filings (annual dummy)	0	0	0

Panel B: Firms *with* pre-VC patent filings

	VC-backed (V/N)		**Differences in means**
	V^1	N^1	
Firm size (log. assets)	13.924	14.036	-0.113
Age (in years)	7.814	7.790	0.024
Asset growth	1.117	1.102	0.015
Dep. on ext. finance	-0.761	-0.926	0.165
Current-ratio	1.968	1.953	0.015
Investments (log. capital exp.)	5.339	5.953	-0.561
Patent filing (annual dummy)	0.805	0.699	0.106
Patent filings (log. count)	0.670	0.613	0.056
Cit. weighted filings (cits. 3 yrs)	1.863	1.105	0.758***
Cit. weighted filings (cits. 5 yrs)	4.056	2.558	1.498***
Cit. weighted filings (cits. 10 yrs)	8.096	5.240	2.856***
Recency - top 1% (dummy)	0.044	0.016	0.027*
Recency - top 25% (dummy)	0.566	0.519	0.047
Originality (avg.)	0.337	0.350	-0.013
Originality (max.)	0.382	0.391	-0.009

Notes: The table provides summary statistics on financial and patenting variables for the five pre-VC years. The table compares the firm groups as defined in Section 2.2. Specifically, Panel A (B) compares firms without (with) patenting activities prior to initial VC investment using the average of the two pre-VC investment years. Further each table reports the mean values for those firms that eventually receive VC financing to those that do not. For the latter, the initial VC investment year is an artificial year as calculated in our matching procedure (see Section 3.1). Firm-level financial variables include information on size (measured as the logarithm of total assets), age, asset growth, the dependence on external financing (measured as the RZ-score defined by Rajan and Zingales 1998), the current ratio, and capital investments (using the log). The patenting variables are only reported for firms that actually patent prior to initial VC financing and include a dummy indicating whether a firm filed a patent application in a given year, the log. number of patent filings, three citation weighted patent filing counts (differentiating among citations received within 3-, 5-, and 10-years after filing), a recency variable measuring the average time lag between the patent filings and their referenced patent filings, and the measures of patent generality and originality, which measure the technological scope of patents (see Hall *et al.* (2001)). Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 2: Firm Distributions

Panel A: Country Distribution

	Obs.	in %	Cumulative Share
Austria	96	1.00	1.00
Belgium	366	3.81	4.81
Germany	1,230	12.79	17.60
Denmark	348	3.62	21.22
Spain	746	7.76	28.98
Finland	522	5.43	34.41
France	2,582	26.86	61.26
Great Britain	1,852	19.26	80.53
Greece	36	0.37	80.90
Hungary	10	0.10	81.01
Ireland	118	1.23	82.23
Italy	254	2.64	84.88
Netherlands	636	6.62	91.49
Portugal	230	2.39	93.88
Sweden	588	6.12	100.00
Total	9,614	100.00	

Panel B: Industry Distribution

	Obs.	in %	Cumulative Share
Information and communication	2,540	26.42	26.42
Manufacturing	1,958	20.37	46.79
Scientific and technical activities	1,876	19.51	66.30
Wholesale and retail trade	1,100	11.44	77.74
Financial and insurance activities	622	6.47	84.21
Admin and support service activities	523	5.44	89.65
Other Industries	995	10.35	100.00
Total	9,614	100.00	

Notes: The table provides summary statistics on the distribution of firms. Panel A depicts the distribution across European countries. The first column shows absolute numbers, while the second and third column show the percentage share and the cumulative percentage share respectively. Panel B depicts the distribution of firms across industries. Industries are classified on the basis of NACE Rev.1. NACE Rev. 1 was made compulsory by Council Regulation (EEC) No 3037/90, which was subsequently amended by Commission Regulation (EEC) No 761/93. It is fully harmonized with the industrial classification of the Member States and the United Nations (keine Ahnung ob wir das hier brauchen). The first column depicts absolute numbers, while the second and third column show the percentage share and the cumulative percentage share respectively.

Table 3: Comparing Patenters and non-Patenters concerning VC Activity

	V^0	V^1	**Differences in means**
Age at first funding	7.193	8.177	-0.984**
Funding First Round	4.931	2.902	2.029
Funding All Rounds	6.552	5.804	0.747
Number of Rounds	1.540	1.793	-0.253***

Notes: The table provides summary statistics on Venture Capital and IPO related variables for Venture Capital funded firms. The table compares pre-patenting and non-patenting firms as defined in the Section Literature and conceptual framework. Venture Capital related variables include information on firm age at the first round of funding, the number of funding rounds perceived, the equity amount given in the first round and overall rounds (in Mio Euros). Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 4: Cox Regression: Non-Patenters

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model
VC	3.595***	3.444***	3.351***	3.761***	3.593***
	(0.551)	(0.565)	(0.566)	(0.939)	(0.696)
Size	1.167***	1.210***	1.212***	1.191***	1.255***
	(0.044)	(0.032)	(0.034)	(0.045)	(0.037)
Profitability	0.253***	0.366***	0.369***	0.387***	0.315***
	(0.042)	(0.065)	(0.070)	(0.095)	(0.052)
Cash Flow Ratio	0.990	0.993	0.993	1.003	0.980*
	(0.007)	(0.007)	(0.007)	(0.003)	(0.008)
Debt Ratio	1.006*	1.008**	1.009*	0.981	0.997
	(0.003)	(0.003)	(0.003)	(0.057)	(0.003)
Age	0.979*	0.975**	0.974**	0.961*	0.969**
	(0.010)	(0.009)	(0.009)	(0.019)	(0.010)
Tangibility	0.673	0.520	0.497*	0.364*	0.471**
	(0.165)	(0.177)	(0.164)	(0.165)	(0.128)
Year Effects	No	Yes	No	No	No
Country Effects	No	Yes	Yes	Yes	Yes
Industry Effects	No	Yes	Yes	Yes	Yes
Country Year Effects	No	No	Yes	Yes	Yes
Manufacturing	Yes	Yes	Yes	No	Yes
N	24422	24422	24422	19123	25723

Standard errors are clustered at 4 Digit Nace Level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

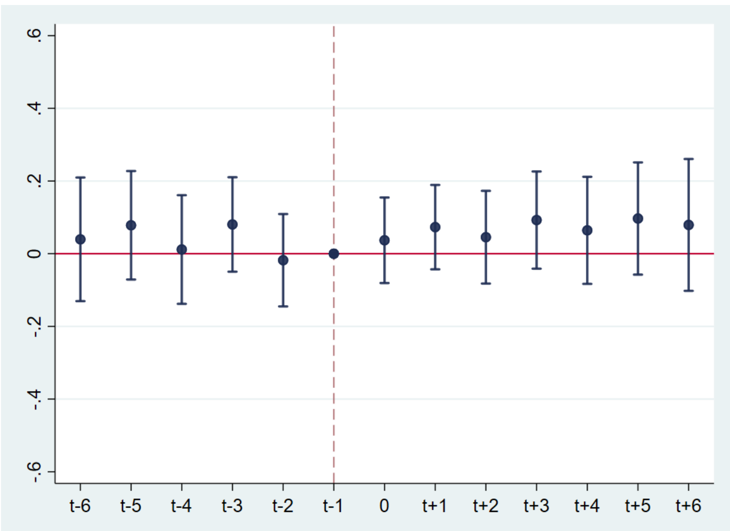
Notes: In this table we present the results of our semiparametric survival approach. All five models display Cox regressions with the left hand side representing the time since the initial round of VC financing. All regressions include the binary variable VC, indicating whether a firm receives funding or not. Moreover we include a set of firm characteristics and several fixed effects. The data in column (1)-(4) is set up such that firms drop out of the dataset after the first failure. Column (5) allows for multiple failures in order to address the concern that one time patenting could be random. Firms in the manufacturing sector are excluded in Column (4) to control for a possible upwards bias through this highly patent intensive sector. Standard errors are clustered at 4 Digit Nace Level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 5: Assessing the Accelerating Effect (Pre-VC Patenters - matched sample)

Panel A: Baseline difference-in-difference estimations

Dep. variable:	Log. patent filings				
	(1)	(2)	(3)	(4)	(5)
VC × Post	0.037	0.024	0.061	0.028	
	(0.040)	(0.062)	(0.053)	(0.043)	
VC	0.037	0.069	0.006	0.039	
	(0.029)	(0.045)	(0.039)	(0.029)	
Post	-0.075**	-0.057	-0.085*	-0.070**	
	(0.031)	(0.050)	(0.043)	(0.034)	
VC × $Pre^{-3,-1}$					-0.063
					(0.050)
VC × $Post^{0,2}$					-0.005
					(0.050)
VC × $Post^{\geq 3}$					0.030
					(0.063)
Sample:	Full	Manuf.	Non-Manuf.	No-Crisis	Full
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
R^2	0.11	0.14	0.12	0.11	0.42
Obs.	4,862	2,271	2,577	4,192	4,862

Panel B: Event-study approach



Notes: This table displays the results of the Difference-in-Differences approach as described in Section 3.3. The dependent variable is the logarithm of the number of patent applications each year. The dummy variable VC is equal to 1 if a firm receives funding for the first time in the observation period t and all subsequent periods and 0 otherwise. *Post* is a firm-specific dummy variable that equals 1 for all years following the initial investment. VC x *post* is the main variable of interest and captures the average additional effect of receiving VC on the dependent variable. Standard errors are clustered at 4 Digit Nace Level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 6: Actual and Hypothetical Patent Filings for VC vs. Non-VC-backed Firms

	Actual Filings	**Predicted Filings**	**Differences in means**
Panel A: Funded firms *without* pre-VC patent filings			
Filings in t=1	0.037	0.012	-0.025***
Filings in t=2	0.040	0.013	-0.027***
Filings in t=3	0.042	0.014	-0.028***
Filings in t=4	0.049	0.014	-0.034***
Filings in t=5	0.054	0.014	-0.039***
Filings in t=6	0.057	0.015	-0.042***
Filings in t=7	0.069	0.014	-0.054***
Filings in t=8	0.043	0.014	-0.028***
Filings in t=9	0.033	0.016	-0.017**
Panel B: Non-funded firms *without* pre-VC patent filings			
Filings in t=1	0.003	0.015	0.012***
Filings in t=2	0.006	0.016	0.009***
Filings in t=3	0.007	0.015	0.008***
Filings in t=4	0.009	0.016	0.016***
Filings in t=5	0.007	0.016	0.009***
Filings in t=6	0.006	0.016	0.009***
Filings in t=7	0.008	0.018	0.009**
Filings in t=8	0.009	0.018	0.008**
Filings in t=9	0.015	0.019	0.003
Panel C: Funded firms *with* pre-VC patent filings			
Filings in t=1	0.395	0.361	-0.034
Filings in t=2	0.365	0.365	-0.000
Filings in t=3	0.401	0.368	-0.033
Filings in t=4	0.415	0.375	-0.040
Filings in t=5	0.387	0.370	-0.017
Filings in t=6	0.389	0.329	-0.059
Filings in t=7	0.406	0.327	-0.079
Filings in t=8	0.297	0.290	-0.006
Filings in t=9	0.433	0.288	-0.144
Panel D: Non-funded firms *with* pre-VC patent filings			
Filings in t=1	0.291	0.392	0.100***
Filings in t=2	0.279	0.386	0.106***
Filings in t=3	0.260	0.380	0.119***
Filings in t=4	0.278	0.385	0.107***
Filings in t=5	0.201	0.375	0.375***
Filings in t=6	0.217	0.343	0.125***
Filings in t=7	0.279	0.322	0.0432
Filings in t=8	0.170	0.304	0.134**
Filings in t=9	0.193	0.280	0.086

Notes: This table reports the results from the second stage of an endogenous switching regression model, the associated "what-if" analysis. The dependent variable in the first stage (unreported) is whether or not a firm gets VC financing in a given year (VC Dummy). The dependent variable in the second-stage regression (unreported) is the logarithm of the number of patent filings in a given year. The independent variables in these regressions comprise the Inverse Mills Ratio from the first stage and all the independent variables and fixed-effects from the semiparametric survival analysis. Panel A reports the results of the "what analysis" for VC funded firms that have not filed for a patent before the initial round of funding, Panel B displays results for the non-backed counterparts. Panel C shows the results for VC funded firms that have been actively patenting before the funding, Panel D for their non-backed counterparts. All Panels report the actual logarithm of the number of patent filings each year, the hypothetical number, and the difference between the actual und the hypothetical values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent level, respectively.

Table 7: Actual and Hypothetical Patent Citations for VC vs. Non-VC-backed Firms

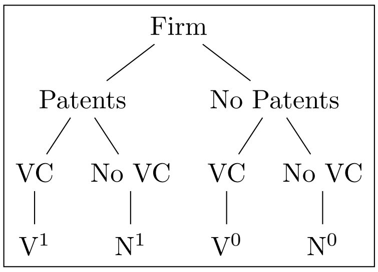
	Actual Citations	**Predicted Citations**	**Differences in means**
Panel A: Funded firms *without* pre-VC patent filings			
Filings in t=1	0.054	0.011	-0.044***
Filings in t=2	0.054	0.011	-0.043***
Filings in t=3	0.060	0.012	-0.049***
Filings in t=4	0.064	0.013	-0.051***
Filings in t=5	0.068	0.014	-0.055***
Filings in t=6	0.077	0.015	-0.063***
Filings in t=7	0.081	0.015	-0.065***
Filings in t=8	0.053	0.016	-0.036***
Filings in t=9	0.049	0.017	-0.033***
Panel B: Non-funded firms *without* pre-VC patent filings			
Filings in t=1	0.004	0.364	0.012***
Filings in t=2	0.004	0.335	0.009***
Filings in t=3	0.009	0.314	0.008***
Filings in t=4	0.010	0.283	0.016***
Filings in t=5	0.007	0.256	0.009***
Filings in t=6	0.006	0.243	0.009***
Filings in t=7	0.008	0.223	0.009**
Filings in t=8	0.005	0.204	0.008**
Filings in t=9	0.009	0.182	0.003***
Panel C: Funded firms *with* pre-VC patent filings			
Filings in t=1	0.527	0.355	-0.171***
Filings in t=2	0.520	0.328	-0.192***
Filings in t=3	0.578	0.321	-0.256***
Filings in t=4	0.552	0.304	-0.247***
Filings in t=5	0.463	0.267	-0.197**
Filings in t=6	0.417	0.221	-0.196**
Filings in t=7	0.475	0.191	-0.284***
Filings in t=8	0.404	0.141	-0.263**
Filings in t=9	0.499	0.119	-0.380***
Panel D: Non-funded firms *with* pre-VC patent filings			
Filings in t=1	0.317	0.477	0.160***
Filings in t=2	0.235	0.457	0.223***
Filings in t=3	0.319	0.424	0.104*
Filings in t=4	0.337	0.431	0.094
Filings in t=5	0.241	0.373	0.132*
Filings in t=6	0.233	0.321	0.088
Filings in t=7	0.309	0.296	-0.013
Filings in t=8	0.284	0.241	-0.043
Filings in t=9	0.228	0.216	-0.012

Notes: This table reports the results from the second stage of an endogenous switching regression model, the associated "what-if" analysis. The dependent variable in the first stage (unreported) is whether or not a firm gets VC financing in a given year (VC Dummy). The dependent variable in the second-stage regression (unreported) is the logarithm of the number of citations received in a time span of five years for a patent filed in the respective year after funding. The independent variables in these regressions comprise the Inverse Mills Ratio from the first stage and all the independent variables and fixed-effects from the semi-parametric survival analysis. Panel A reports the results of the "what analysis" for VC funded firms that have not filed for a patent before the initial round of funding, Panel B displays results for the non-backed counterparts. Panel C shows the results for VC funded firms that have been actively patenting before the funding, Panel D for their non-backed counterparts. All Panels report the actual logarithm of the number of citations received in a time span of five years for a patent filed in the respective year after funding, the hypothetical number, and the difference between the actual und the hypothetical values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent level, respectively.

Figures from the main part

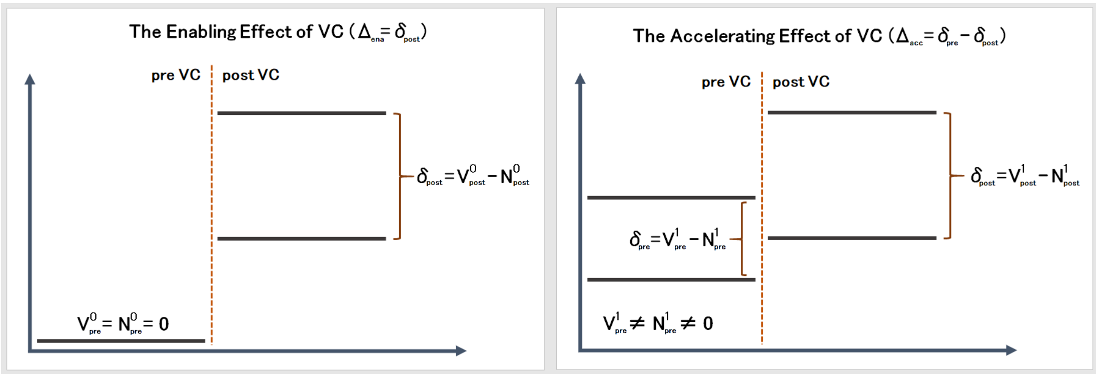
Figure 1: Graphical illustrations of the conceptual framework

Panel A: Defining different firm types regarding patenting and VC activities



	VC funding	No VC funding
Patents	V^1	N^1
No Patents	V^0	N^0

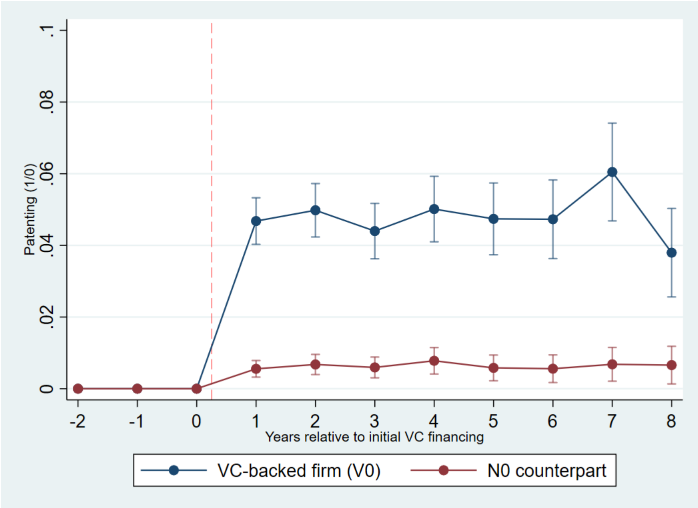
Panel B: Illustrating the Enabling and Accelerating Effects of VC



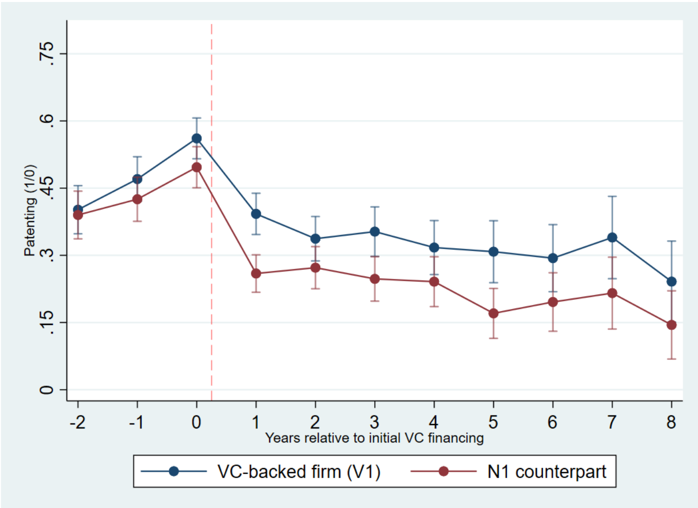
Notes: These Figures illustrate conceptually the methodological framework of our empicial strategy. Panel A illustrates graphically how we distinguish the different firm types relevant for our conceptual framework, as outlined in section 2.2. Panel B is a graphical illustration of the two main effects, the enabling and the accelerating effect of VCs, as described in section 2.2.

Figure 2: Potential Enabling and Accelerating Effect - Extensive Margin

Panel A: Potential Enabling of Non-Patenting Firms



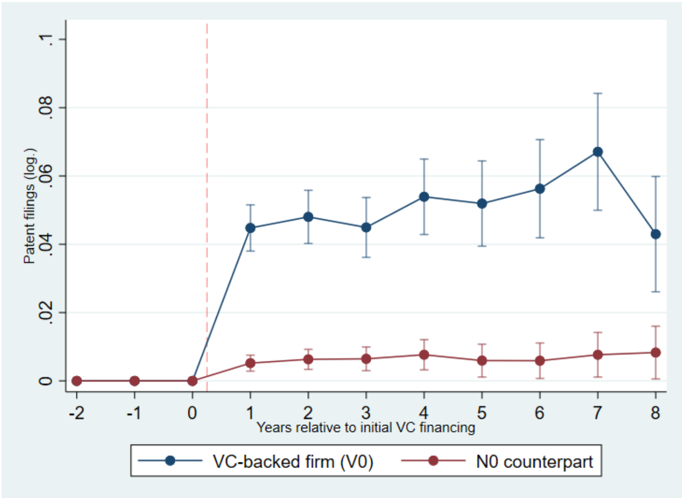
Panel B: Potential Accelerating of Patenting Firms



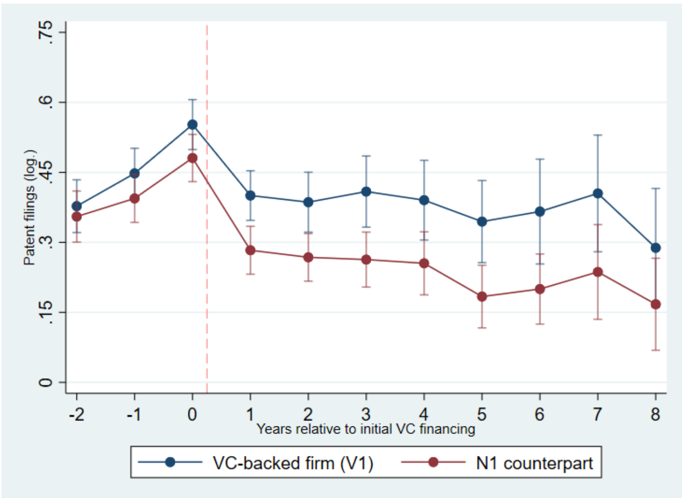
Notes: These Figures examine the potential enabling and accelerating effect as defined in 2.2. Both Panels indicate, which percentage share of firms filed at least one patent each year. Panel A comprises the firms that have not filed patents before the initial round of funding and their non-backed counterparts two years before and eight years following the first funding. Panel B comprises firms that have filed patents before the initial round of funding and their non-backed counterparts in the same time-span.

Figure 3: Potential Enabling and Accelerating Effect - Intensive Margin

Panel A: Potential Enabling of Non-Patenting Firms

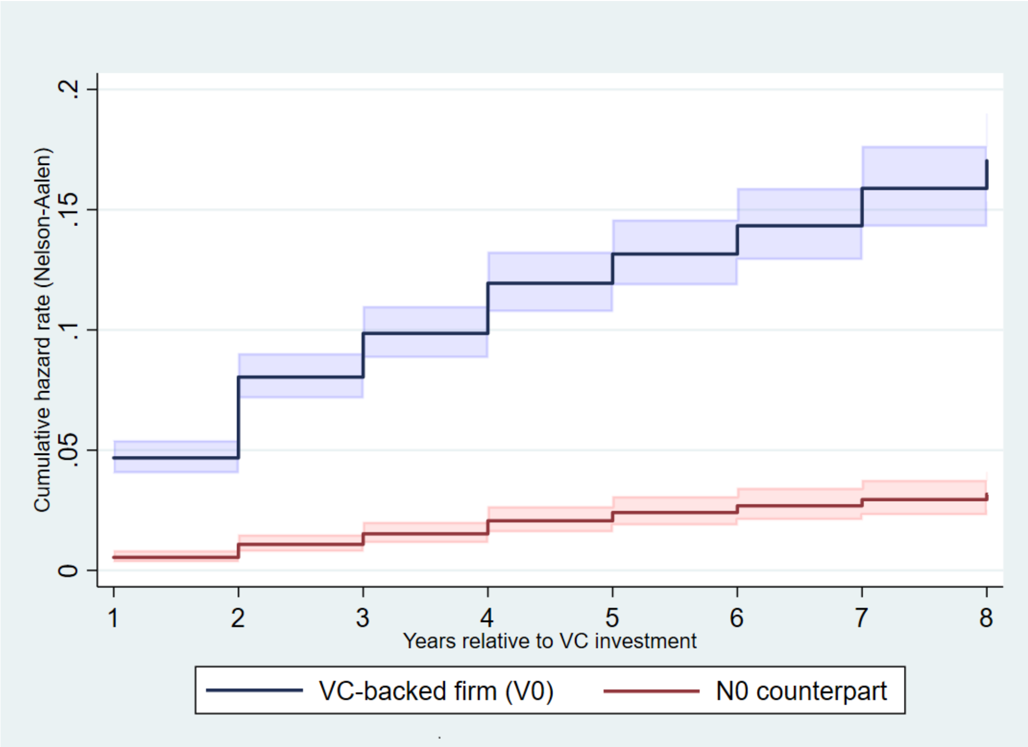


Panel B: Potential Accelerating of Patenting Firms



Notes: These Figures examine the potential enabling and accelerating effect as defined in 2.2. Panel A displays the logarithm of patent applications each year for firms that have not filed patents before the initial round of funding and for their non-backed counterparts two years before and eight years following the first funding. Panel B displays the logarithm of patent applications each year for firms that have filed patents before the initial round of funding and for their non-backed counterparts in the same time-span.

Figure 4: Non-Patenters: Cumulative Hazard Estimates



Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus the control group. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while their non-backed comprise the control group. Firms drop out of the dataset right after they filed their first patent.

FOR ONLINE PUBLICATION

Internet Appendix A : Tables

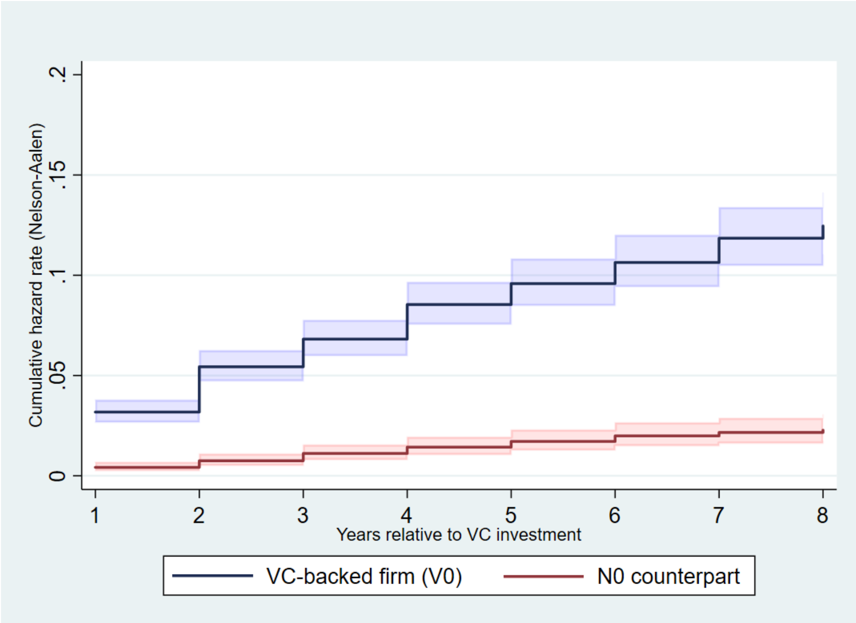
Table IA1: Actual and Predicted Average Patent Citations for VC vs. Non-VC-backed Firms

	Actual Avg. Citations	**Predicted Avg. Citations**	**Differences in means**
Panel A: Funded firms *without* pre-VC patent filings			
Filings in t=1	0.160	0.016	-0.145***
Filings in t=2	0.153	0.017	-0.136***
Filings in t=3	0.156	0.018	-0.138***
Filings in t=4	0.154	0.020	-0.134***
Filings in t=5	0.207	0.022	-0.186***
Filings in t=6	0.148	0.024	-0.125***
Filings in t=7	0.145	0.025	-0.120***
Filings in t=8	0.098	0.027	-0.071***
Filings in t=9	0.105	0.028	-0.076**
Panel B: Non-funded firms *without* pre-VC patent filings			
Filings in t=1	0.008	1.351	1.343***
Filings in t=2	0.006	1.240	1.234***
Filings in t=3	0.014	1.161	1.146***
Filings in t=4	0.018	1.038	1.019***
Filings in t=5	0.010	0.934	0.924***
Filings in t=6	0.007	0.883	0.877***
Filings in t=7	0.804	0.804	0.791***
Filings in t=8	0.008	0.733	0.724***
Filings in t=9	0.014	0.649	0.635***
Panel C: Funded firms *with* pre-VC patent filings			
Filings in t=1	1.522	1.247	-0.275
Filings in t=2	1.101	1.151	0.050
Filings in t=3	1.327	1.130	-0.196
Filings in t=4	1.128	1.049	-0.079
Filings in t=5	0.799	0.928	0.129
Filings in t=6	0.604	0.852	0.248
Filings in t=7	1.299	0.762	-0.536
Filings in t=8	1.015	0.622	-0.394
Filings in t=9	0.843	0.510	-0.333
Panel D: Non-funded firms *with* pre-VC patent filings			
Filings in t=1	0.611	1.117	0.506***
Filings in t=2	0.481	1.125	0.644***
Filings in t=3	0.794	1.087	0.293
Filings in t=4	0.913	1.088	0.175
Filings in t=5	0.447	1.026	0.579***
Filings in t=6	0.372	0.852	0.480***
Filings in t=7	0.948	0.791	-0.158
Filings in t=8	0.894	0.731	-0.163
Filings in t=9	0.391	0.682	0.291

Notes: This table reports the results from the second stage of an endogenous switching regression model, the associated "what-if" analysis. The dependent variable in the first stage (unreported) is whether or not a firm gets VC financing in a given year (VC Dummy). The dependent variable in the second-stage regression (unreported) is the average number of citations received in a time-span of five years for a patent filed in the respective year after funding. The independent variables in these regressions comprise the Inverse Mills Ratio from the first stage and all the independent variables and fixed-effects from the semiparametric survival analysis. Panel A reports the results of the "what analysis" for VC funded firms that have not filed for a patent before the initial round of funding, Panel B displays results for the non-backed counterparts. Panel C shows the results for VC funded firms that have been actively patenting before the funding, Panel D for their non-backed counterparts. All Panels report the actual average number of citations received in a time-span of five years for a patent filed in the respective year after funding, the hypothetical number, and the difference between the actual und the hypothetical values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent level, respectively.

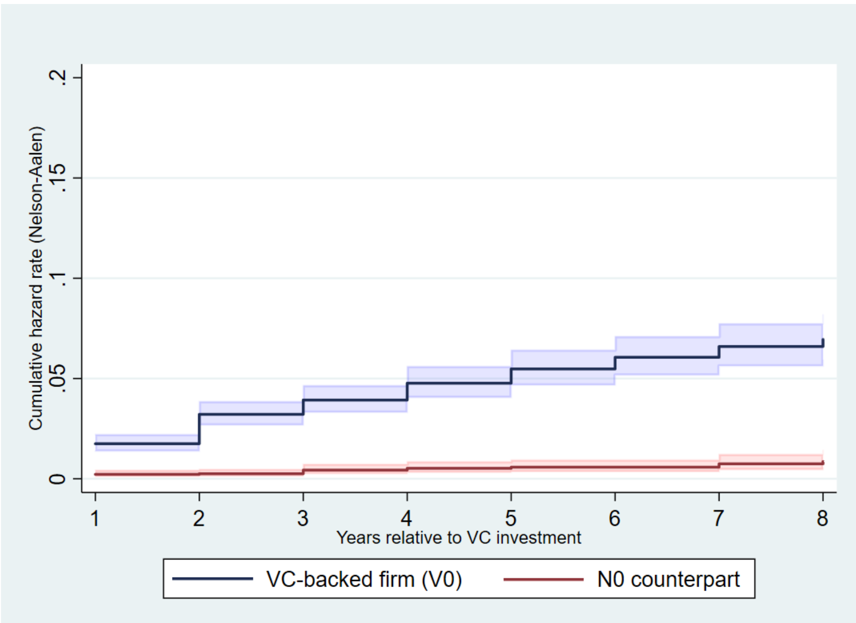
Internet Appendix B : Figures

Table IA1: Non-Patenters: Cumulative hazard estimates for patents that received at least one citation



Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus control group. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while their non-backed comprise the control group. Firms drop out of the dataset right after they filed their first patent. These estimations only include patents that have received at least one citation in the five years following the application and can thus be refered to as patents with impact.

Table IA2: Non-Patenters: Cumulative hazard estimates for patents that received more than medium citations



Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus control group. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while their non-backed comprise the control group. Firms drop out of the dataset right after they filed their first patent. These estimations only include patents that have received more than medium citations in the five years following the application and can thus be refered to as patents with high impact.